Online Learning and Management of Future Power Grids

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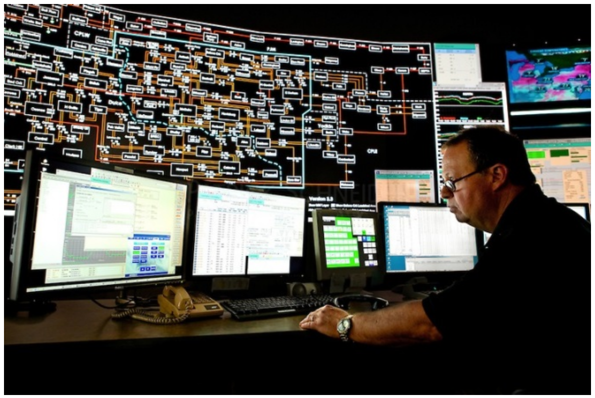
Acknowledgements: NSF 1423316, 1442686, 1509040; V. Kekatos (VT), S.-J. Kim (UMBC), A.-J. Conejo (OSU), G. Wang (UMN)

Denver, CO
January 27, 2016

Smart Grid: Advanced infrastructure leveraging information technologies to enhance the current electrical power networks



controllable

resilient

efficient

participation

sustainable

self-restoring

green

situational awareness

US Dept. of Energy, “The smart grid: An introduction,” 2009.

Enabling technology advances

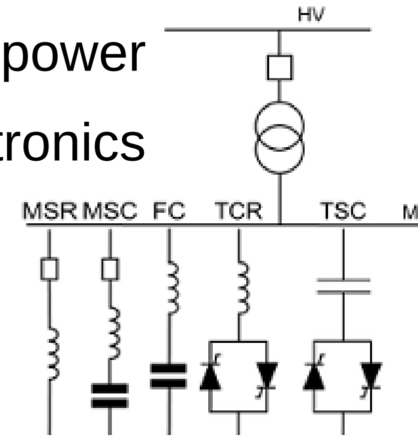
distributed generation

micro-grids

renewables

power

electronics



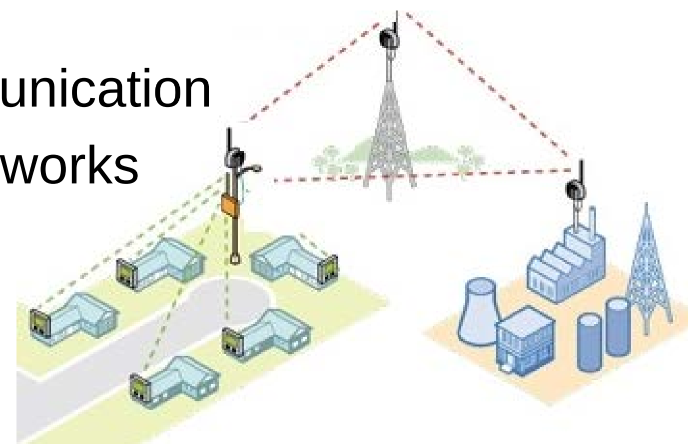
Learning, optimization, and signal processing toolbox

sensing/metering

electric vehicles

demand response

communication networks



Roadmap

- Online power system state estimation (PSSE)
  - Semi-definite relaxation (SDR) for nonlinear PSSE
  - Online convex optimization (OCO) via mirror descent algorithm
- Real-time pricing for demand response (DR)
  - Full/partial (bandit) feedback
- Stochastic energy management
  - Stochastic reactive power control
  - Joint active and reactive power control
  - Leveraging voltage regulation and inverter flexibilities

Online PSSE

- Static PSSE
  - For steady-state; no dynamics; hence, adequate for conventional grids
- Dynamic PSSE
  - Incorporates measurement history/predicts states using dynamical models
  - Dynamical models may be hard to obtain under high penetration of renewables
- Challenges
  - Non-convexity due to nonlinear measurements (local optimality)
  - Model uncertainty and non-stationarity
- Technical approaches
  - Semidefinite programming relaxation [Zhu-Giannakis'11, Lavaei-Low'11]
  - Online convex optimization [Kim-Wang-Giannakis'14]

G. B. Giannakis, V. Kekatos, N. Gatsis, S.-J. Kim, H. Zhu, and B. Wollenberg, **"**Monitoring and optimization for power grids: A signal processing perspective," *IEEE SP Magazine,* pp. 107-128, Sept. 2013.

SDR for batch PSSE

- Static PSSE task (quadratic $h_m(\mathbf{v})$ in general)

$$\min_{\mathbf{v}} \sum_{m=1}^{M} w_m [z_m - h_m(\mathbf{v})]^2$$

  - Nonconvex and generally NP-hard to solve

- SDP-based approach
  - If $\mathbf{x} := [\Re(\mathbf{v})^{\mathcal{T}} \ \Im(\mathbf{v})^{\mathcal{T}}]^{\mathcal{T}}$, and $\mathbf{X} := \mathbf{x}\mathbf{x}^{\mathcal{T}}$, then $h_m(\mathbf{v}) = \mathrm{tr}(\mathbf{H}_m\mathbf{X})$
  - Equivalent formulation

$$\begin{aligned} \min_{\mathbf{X}} \quad & \sum_{m=1}^{M} \omega_m \left[z_m - \mathrm{Tr}(\mathbf{H}_m\mathbf{X})\right]^2 \\ \text{s.t.} \quad & \mathbf{X} \succeq \mathbf{0} \\ & \mathrm{rank}(\mathbf{X}) = 1 \end{aligned}$$

H. Zhu and G. B. Giannakis, "Estimating the state of AC power systems using semidefinite programming," in *Proc. of the North American Power Symposium*, Boston, MA, Aug. 2011.

Online convex optimization

- OCO framework: game between a player and an adversary
  - At each time slot $t = 0, 1, \ldots, T$
  - Utility (player) chooses $\mathbf{X}^t$
  - Grid (adversary) chooses $c^t(\mathbf{X}) := \sum_{m=1}^{M} w_m [z_m^t - \mathrm{tr}(\mathbf{H}_m \mathbf{X})]^2$
  - Player suffers loss $c^t(\mathbf{X}^t)$

- **OCO goal:** achieve *sublinear* regret

$$R_c(T) := \sum_{t=1}^{T} c^t(\mathbf{X}^t) - \min_{\mathbf{X} \in \mathcal{X}} \sum_{t=1}^{T} c^t(\mathbf{X}) \text{ with } R_c(T)/T \to 0 \text{ as } T \to \infty$$

Online PSSE using OCO

- Dynamic PSSE as a game between the utility and the grid buses
- **Goal**: choose $\mathbf{X}^t \succeq \mathbf{0}$ at each time t to minimize $\sum_{t=1}^{T} c^t(\mathbf{X}^t)$

$$c^t(\mathbf{X}) := \sum_{m=1}^{M} w_m [z_m^t - \mathrm{tr}(\mathbf{H}_m \mathbf{X})]^2$$

- Online mirror descent achieves sublinear regret [Shalev-Shwartz'12]

$$\mathbf{X}^{t+1} = \arg\min_{\mathbf{X}\succeq 0} \langle \nabla c^t(\mathbf{X}^t), \mathbf{X} \rangle + \frac{1}{\eta^t} D(\mathbf{X}, \mathbf{X}^t)$$

η^t: stepsize
$D(\cdot,\cdot)$: Bregman div.

- Choosing $D(\mathbf{X},\mathbf{Y}) := \frac{1}{2}\|\mathbf{X}-\mathbf{Y}\|_F^2$ yields

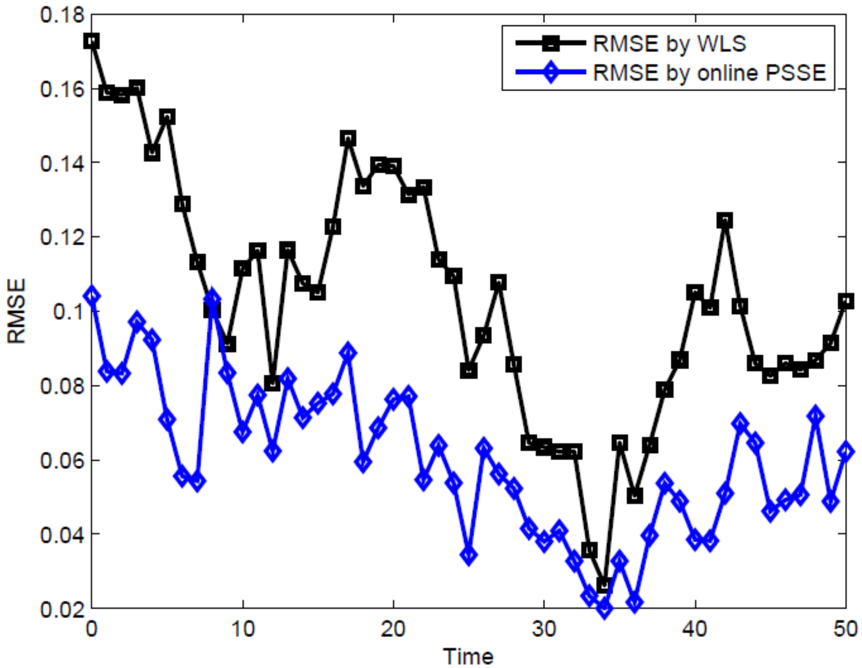
$$\boxed{\mathbf{X}^{t+1} = \arg\max_{\mathbf{X}\succeq 0} \left\{ \sum_{m=1}^{M} 2w_m [z_m^t - \mathrm{tr}(\mathbf{H}_m \mathbf{X}^t)] \mathrm{tr}(\mathbf{H}_m \mathbf{X}) + \frac{1}{2\eta^t} \|\mathbf{X} - \mathbf{X}^t\|_F^2 \right\}}$$

  - Completing the squares offers closed-form updates

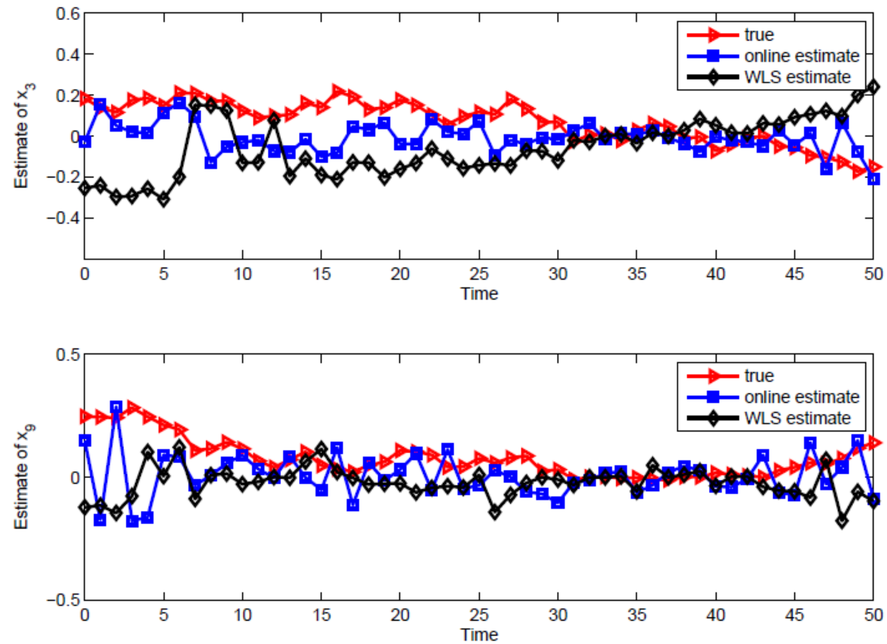
S.-J. Kim, G. Wang, and G. B. Giannakis, "Online semidefinite programming for power system state estimation," *Proc. of Intl. Conf. on Acoust., Speech, and Signal Process.*, Florence, Italy, May 2014.

PSSE tests with IEEE 6-bus system

- Random walk dynamical model: $\mathbf{v}^{t+1} = \rho \mathbf{v}^t + \boldsymbol{\eta}^t, \;\; \rho = 0.99$



RMSE performance

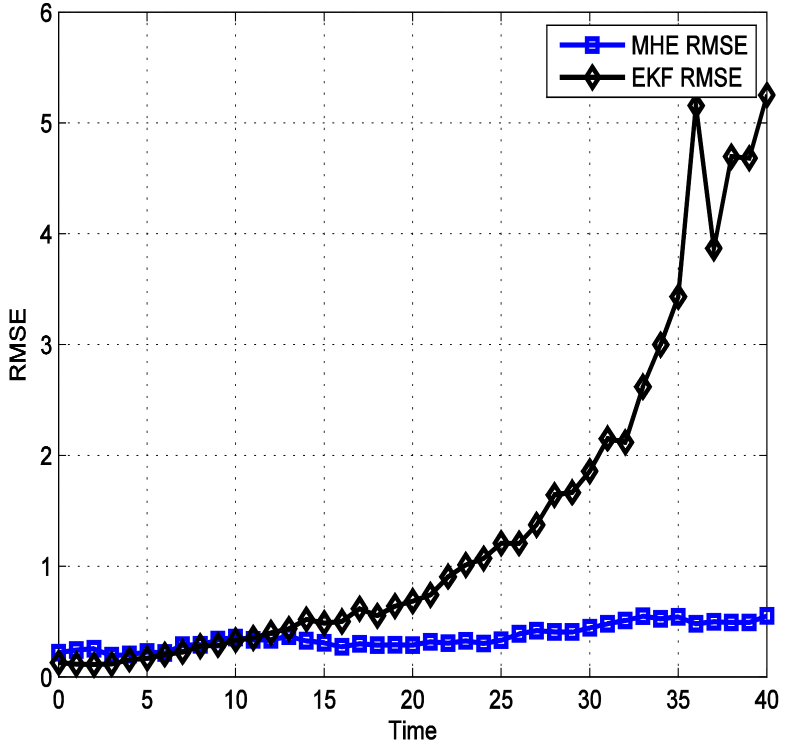


Real and imaginary parts of v_3^t

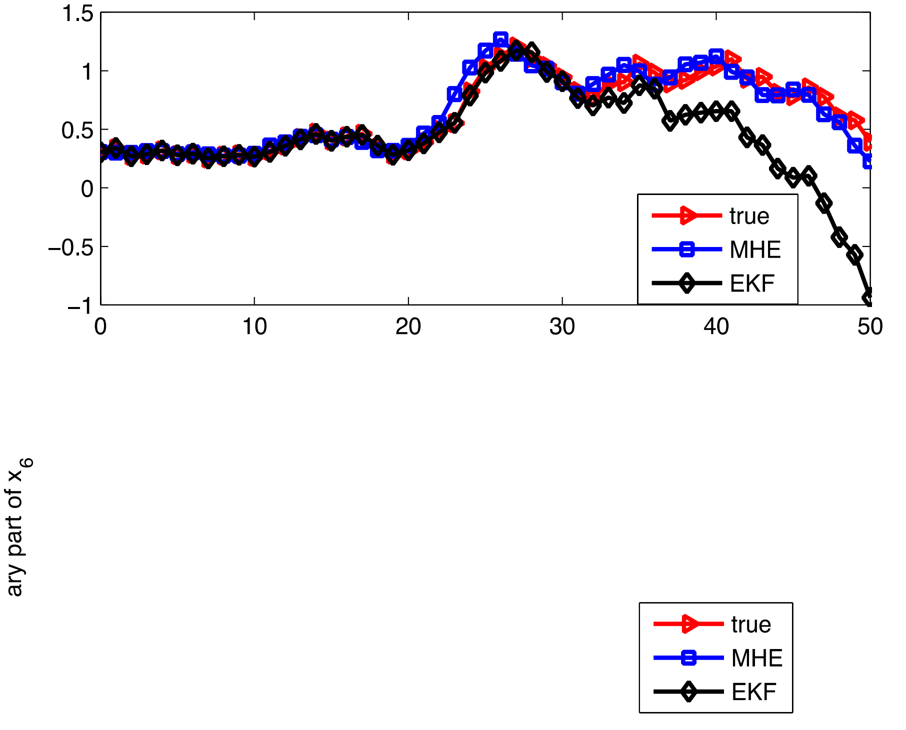
- Albeit “blind” to dynamics, OCO outperforms WLS for online PSSE

Moving-horizon PSSE

- Leveraging state-space model $\boldsymbol{v}^{t+1} = \rho \boldsymbol{v}^t + \boldsymbol{w}^t, \;\; y_i^t = h_i(\boldsymbol{v}^t) + \eta_i^t$



RMSE performance

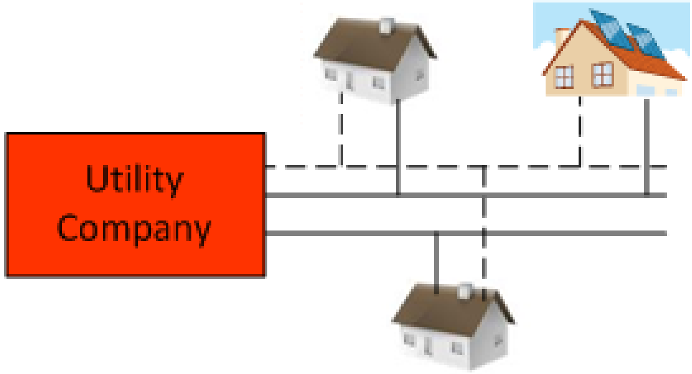


Real and imaginary parts of v_6^t

- MH-based dynamic PSSE outperforms EKF tracker

Real-time pricing for DR

- Adapt load schedules based on load prices



Issues: Privacy, robustness, real-time,
consumer participation

Goal: smart real-time pricing by learning consumer preferences

- Adjust energy price in real-time to shape load
- Set prices differently for individual customers
- Load-price elasticity changes across consumers and time

Challenge: Learn elasticity with minimal "modeling"

Problem formulation

- **Model**
  - p_k^t: price adjustment for customer *k* at time slot *t*
  - l^t : load level at slot *t* *without* price adjustment
  - θ_k^t : elasticity of consumer *k* at slot *t*
  - d_k^t: load adjustment of customer *k* due to price adjustment p_k

$$d_k^t = -\theta_k^t p_k^t \qquad \boldsymbol{\theta}^t := [\theta_1^t, \ldots, \theta_K^t]^\mathsf{T}$$

  - Aggregate adjusted load $$l_a^t := l^t + \sum_k d_k^t = l^t - \boldsymbol{\theta}^{t\,\mathsf{T}} \mathbf{p}^t$$

Goal: minimize load *variance* $$\frac{1}{2}\sum_{t=1}^{T}\left(l^t - \boldsymbol{\theta}^{t\,\mathsf{T}}\mathbf{p}^t - m^t\right)^2$$

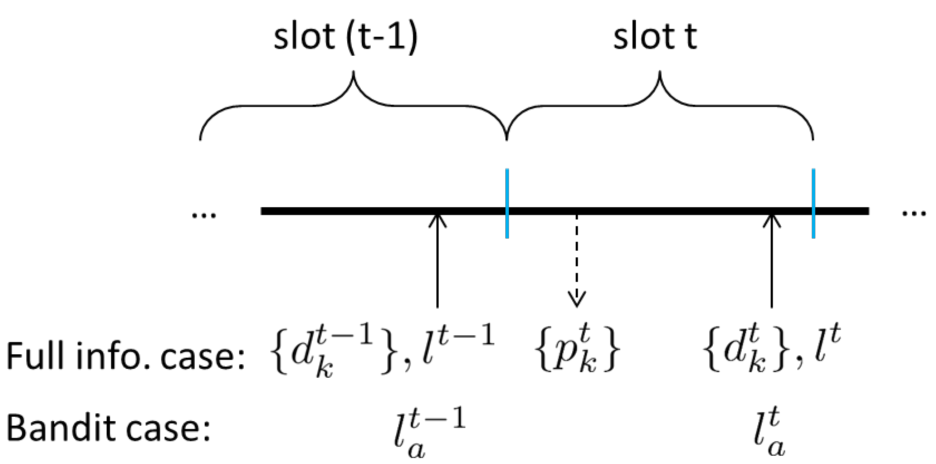
- Promote sparsity and fairness

$$c^t(\mathbf{p}^t) := \underbrace{\frac{1}{2}\left(l^t - \boldsymbol{\theta}^{t\,\mathsf{T}}\mathbf{p}^t - m^t\right)^2}_{:=\phi^t(\mathbf{p}^t)} + \underbrace{\lambda\|\mathbf{p}^t\|_1 + \frac{\mu}{2}\|\mathbf{p}^t\|_2^2}_{:=r(\mathbf{p}^t)}$$

Two types of feedback

- **Full feedback**
  - $F^t = c^t(\cdot)$
  - Utility obtains l^t and $\{d_k^t\}_{k=1}^K$ at the end of slot *t* $(\hat{\theta}_k^t = -d_k^t/(p_k^t + \varepsilon))$

- **Partial (bandit) feedback**
  - $F^t = c^t(p^t)$
  - Utility observes only l_a^t at the end of slot *t*



Algorithms

- Full feedback case

  - Composite objective mirror descent (COMID)

$$\mathbf{p}^{t+1} = \arg\min_{\mathbf{p}\in\mathcal{P}} \left[-\eta \underbrace{(l^t - {\boldsymbol{\theta}^t}^\mathsf{T}\mathbf{p}^t - m^t){\boldsymbol{\theta}^t}^\mathsf{T}}_{\nabla\phi^t(\mathbf{p}^t)}\mathbf{p} + \frac{1}{2}||\mathbf{p}-\mathbf{p}^t||_2^2 + \eta\left(\lambda||\mathbf{p}||_1 + \frac{\mu}{2}||\mathbf{p}||_2^2\right)\right]$$

η : step size

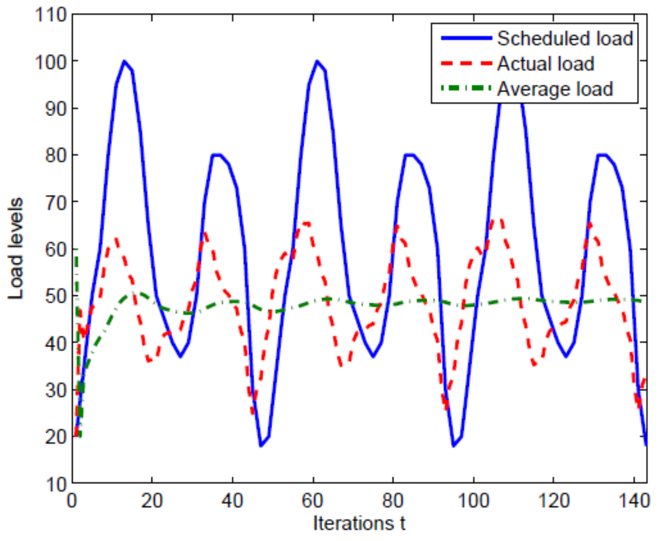
  - Provably achieves $O(\sqrt{T})$ regret bound

- Partial feedback case

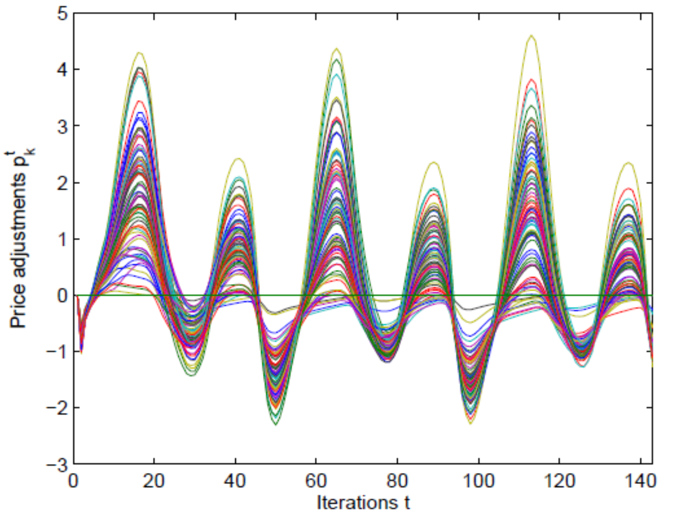
  - Need random sampling to estimate gradient of $c^t(\cdot)$
  - Our algorithm enjoys $O(T^{3/4})$ regret bound [Kim-Giannakis'14]
  - No need to know individual time-varying demands!

S.-J. Kim and G. B. Giannakis, "Real-time electricity pricing for demand response using online convex optimization," *Proc. PES Conf. on Innovative Smart Grid Tech.*, Washington, DC, Feb. 2014.

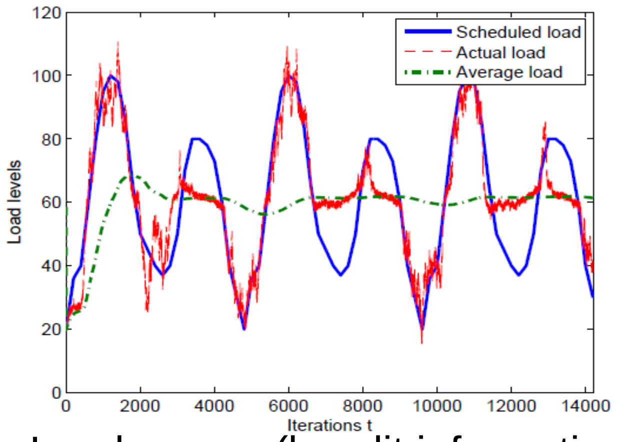
RTP tests



Load before and after real-time DR



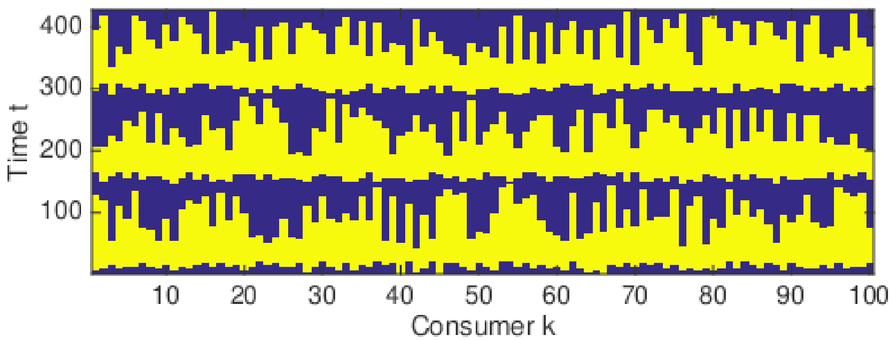
Price adjustment (full information)

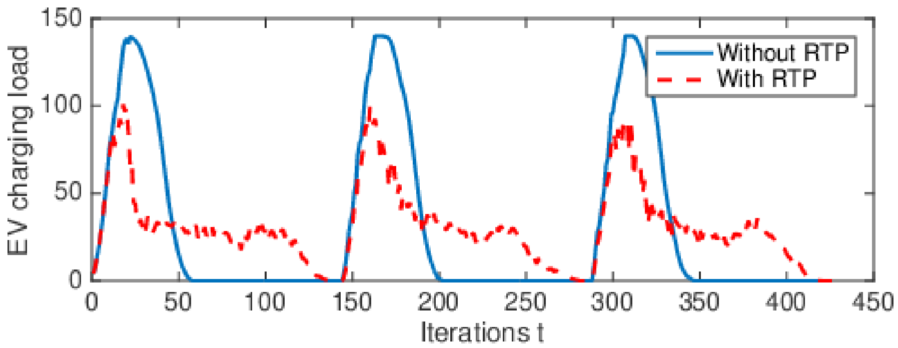


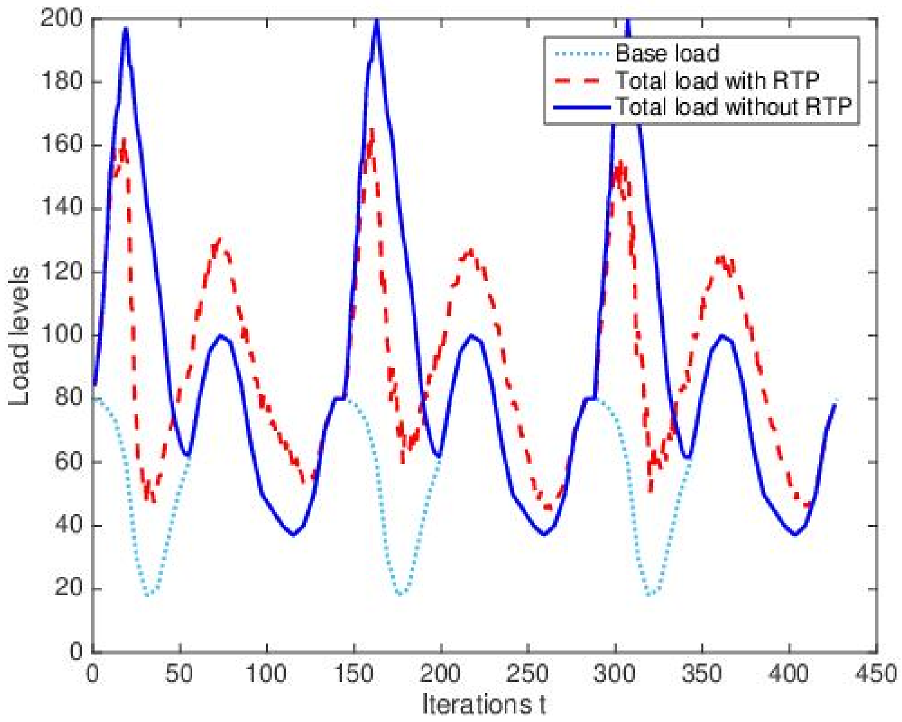
Load curves (bandit information)

RTP with EV charging added

- Charging *K=100* EVs; uniformly over 6-10pm; for 3 days



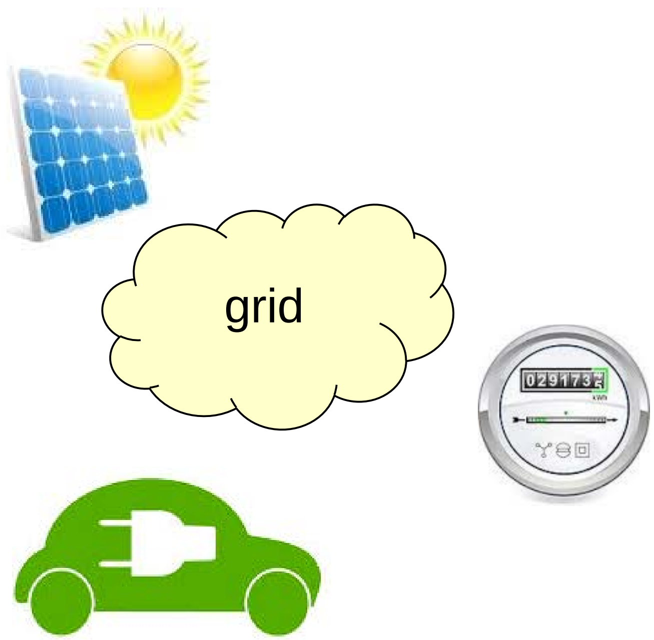




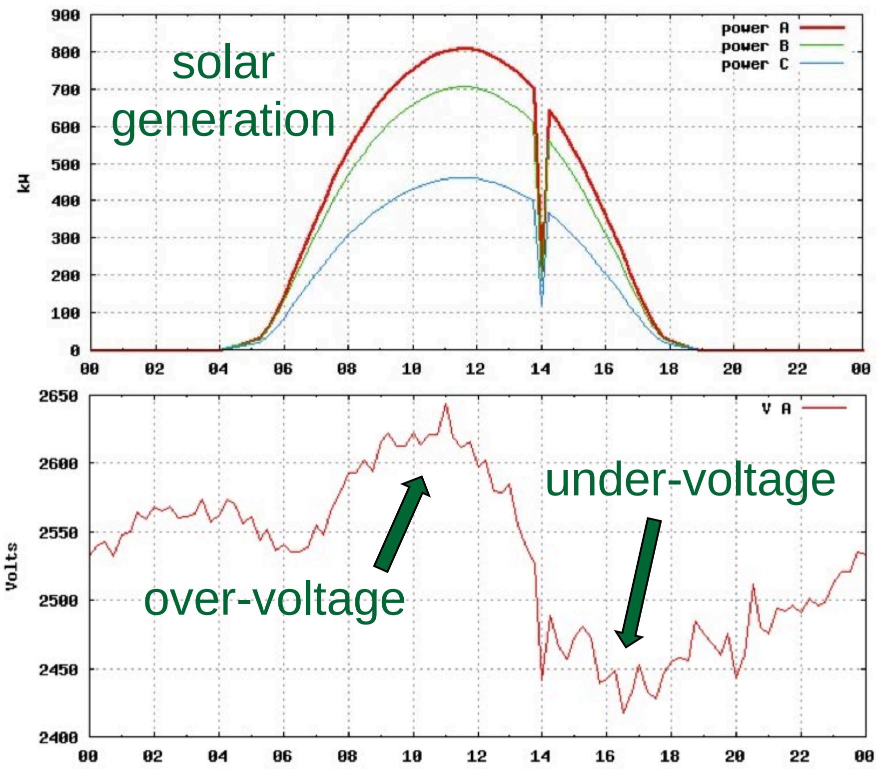
- RTP smooths the overall (base plus EV) load curve

Motivation for stochastic control

- Distribution grids undergo transformative changes



- Active power fluctuations affect voltage magnitudes [25kV]



GridLAB-D: Pacific Northwest National Laboratory, [Online:] www.gridlabd.org/gldportal/

Reactive power management

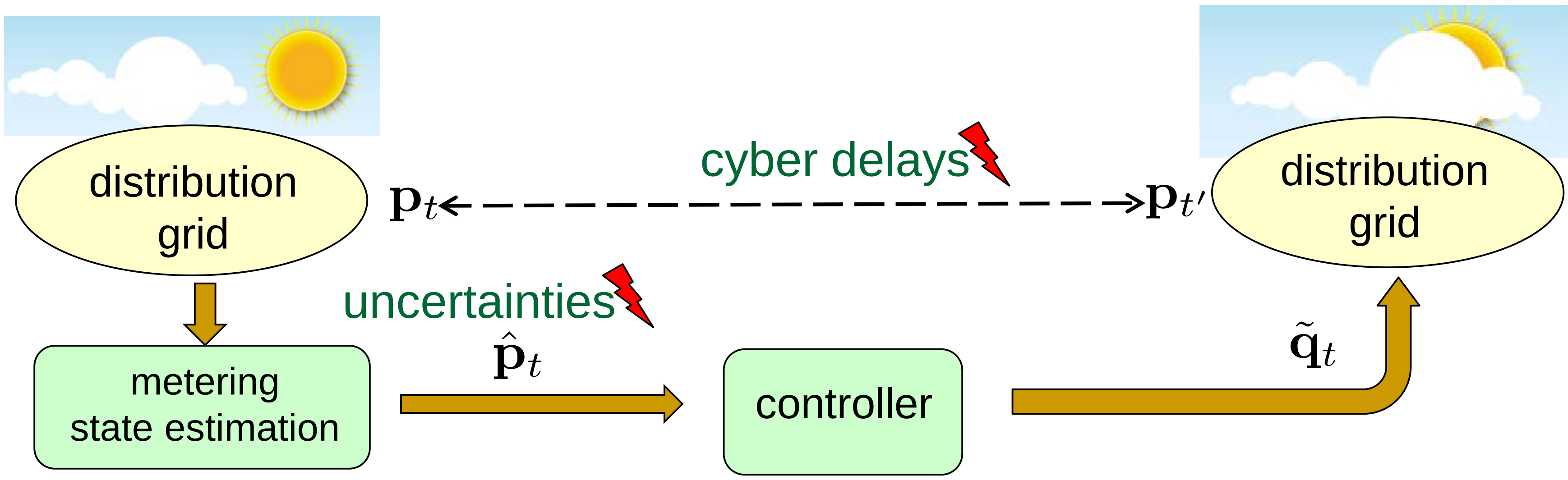
Problem statement: *Given active injections, control reactive injections to minimize losses while preserving voltage magnitudes within desired range*

- Typically performed by utility-owned transformers and capacitors
  - discrete variables, slow response, limited lifetime [Baldick-Wu'90]

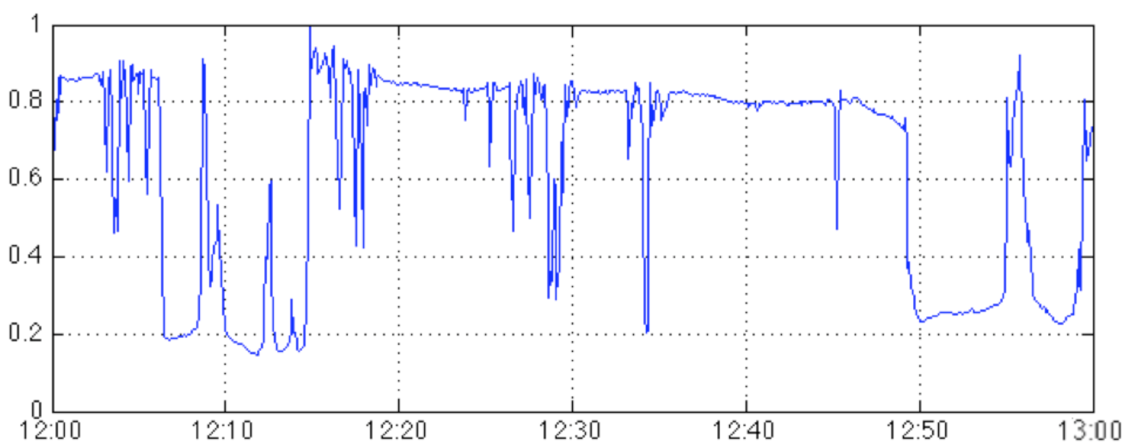
- Reactive control enabled by PV inverters [Overybye'10], [Chertkov'11]
  - decentralized [Baran-Markabi'07], [Robbins-Garcia'13], [Bologniani'13]
  - localized [Zhang-Garcia-Tse'13]; successive approximation [Deshmukh'12]
  - convex relaxations [Lam-Zhang-Tse'12], [Dallanese-Dhople-Giannakis'14]

- ***Presumption:*** *active power injections are known and constant*

Grid operation



generation fluctuations



Online data-based scheme

- Deterministic loss minimization $\tilde{\mathbf{q}}_t := \arg\min_{\mathbf{q}\in\mathcal{Q}} f_t(\mathbf{q}) = f(\mathbf{p}_t, \mathbf{q})$
- Stochastic power loss minimization $\hat{\mathbf{q}} := \arg\min_{\mathbf{q}\in\mathcal{Q}} \mathbb{E}_{\mathbf{p}_t}[f_t(\mathbf{q})]$
- Stochastic approximation method (distribution-free)

$$\hat{\mathbf{q}}_{t+1} := \arg\min_{\mathbf{q}\in\mathcal{Q}} \; f_t(\mathbf{q}_t) + \mathbf{g}_t^T(\mathbf{q} - \mathbf{q}_t) + \frac{1}{2\eta_t}\|\mathbf{q} - \mathbf{q}_t\|_2^2$$

Challenges: finding $\mathbf{g}_t \in \partial f_t(\mathbf{q})$ and the minimizer $\hat{\mathbf{q}}_{t+1}$

- Subdifferential $\partial f_t(\hat{\mathbf{q}}_{t-1})$ coincides with Lagrange multiplier $\boldsymbol{\lambda}_t$

$\boldsymbol{\lambda}_t$

$$f(\mathbf{p},\mathbf{q}) = \min_{\substack{\mathbf{P},\mathbf{Q}\\ \boldsymbol{\ell},\mathbf{v}}} \sum_{n=1}^{L} r_n \ell_n \text{ s.t. } p_n = \sum_{k\in\mathcal{C}_n} P_k - (p_n - r_n\ell_n), q_n = \sum_{k\in\mathcal{C}_n} Q_k - (Q_n - x_n\ell_n)$$

$$v_n = v_{\pi_n} + (r_n^2 + x_n^2)\ell_n - 2(r_nP_n + x_nQ_n), \; \ell_n \geq P_n^2 + Q_n^2, \; \mathbf{v}\in\mathcal{V}$$

V. Kekatos, G. Wang, A. J. Conejo, and G. B. Giannakis, "Stochastic reactive power management in microgrids with renewables," *IEEE Trans. on Power Systems,* pp. 3386-3395, Nov. 2015.

Convergence

If $\|\hat{\mathbf{q}} - \mathbf{q}_t\|_2^2 \le 2D^2,\ \|\boldsymbol{\lambda}\|_2 \le L,\ \forall t$ *and* $\bar{\mathbf{q}}_T := \frac{1}{T}\sum_{t=1}^{T} \hat{\mathbf{q}}_t$ *,it holds that*

(a) $\mathbb{E}\big[F(\overline{\mathbf{q}}_T)\big] - F(\hat{\mathbf{q}}) \le \frac{\alpha D L}{\sqrt{T}}$

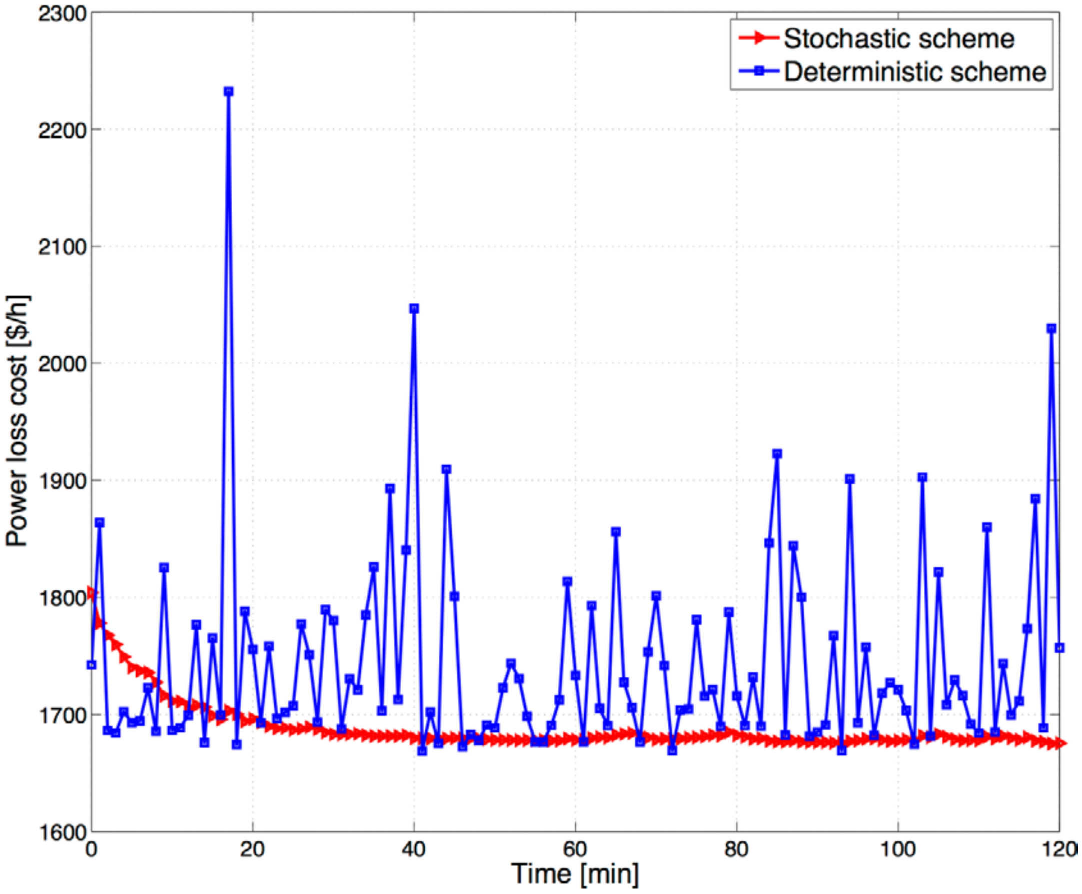
(b) $F(\overline{\mathbf{q}}_T) - F(\hat{\mathbf{q}}) \le \frac{DL}{\sqrt{T}}\big(\alpha + 4\sqrt{\log\delta}\big)$ *with probability* $1 - \delta^{-1}$

where $\alpha = 2$ *for* $\eta_t = \frac{D}{L\sqrt{t}}$ *or* $\alpha = 1.5$ *for* $\eta_t = \frac{D}{L\sqrt{T}}$.

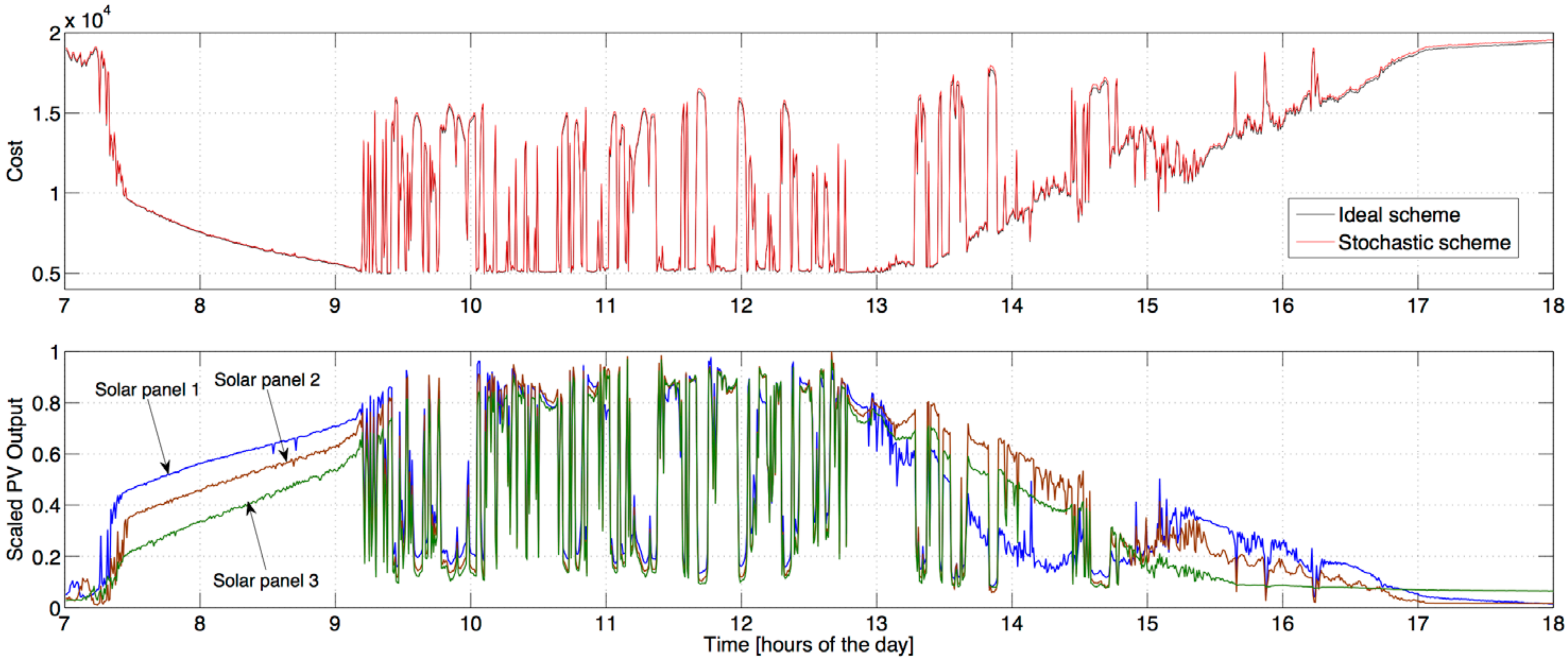
- Sublinear convergence in expectation and in probability
- Constant or diminishing step size η_t
- Compact $\mathcal{Q}$ implies finite (D, L)

Simulated active power uncertainty

- South. Cal. Edison grid: 47 buses and 10 solar generators
- Active power + AWGN; and 30sec control period with 30sec cyber delays



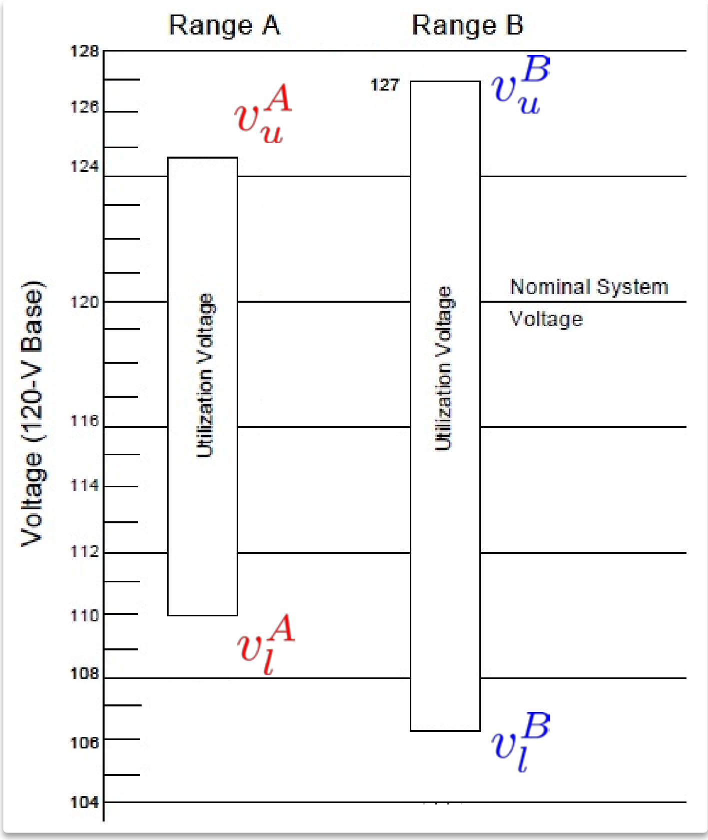
Reactive power control with real data



- Stochastic scheme tracks the ideal (unrealistic) scheme
- Lower cost at periods of local solar generation

Leveraging stochastic constraints

- Flexibility in voltage regulation standards
  - voltage magnitudes in prescribed region for 95% of 10-min samples [EN50160 Std.]
  - two utilization ranges defined by ANSI C84.1



- Flexibility in smart inverters
  - inverters designed to work at 1.2-1.5 times higher nameplate ratings
  - transient overloading possible [Moursi-Xiao-Kirtley'13, ABB'10]

ANSI C84.1-2006 American National Standard for Electric Power Systems and Equipment Voltage Ratings (60 Herz), ANSI, 2011.

Stochastic energy management

Problem statement: *Given consumption and renewable generation predictions, jointly optimize active and reactive injections to minimize losses while balancing the voltage profiles*

- Why active power curtailment?
  - voltage magnitudes sensitive to active injections in distribution grids
  - worldwide feed-in tariff opportunities (successful in Europe and US)
  - wind curtailment level: 2%-40% [NREL'14]
- ***Presumption:*** perfect predictions, deterministic interpretation of standards

Deterministic energy management

$$
\begin{aligned}
J^*_{1,t} := \min_{\mathbf{p}^g_t, \mathbf{q}^g_t} \; & f_t(\mathbf{p}^g_t, \mathbf{q}^g_t) \\
\text{s.to} \;\; & 0 \leq p^g_{n,t} \leq \bar{p}^g_{n,t}, \;\; \forall n \\
& (p^g_{n,t})^2 + (q^g_{n,t})^2 \leq s^2_n, \;\; \forall n \\
& v^A_l \leq v_{n,t}(\mathbf{p}^g_t, \mathbf{q}^g_t) \leq v^A_u, \;\; \forall n
\end{aligned}
$$

curtailed solar energy

inverter power limits

voltage regulation limits

- Presumed operating conditions
  - predictions $(\mathbf{p}^c_t, \mathbf{q}^c_t, \bar{\mathbf{p}}^g_t)$ are precisely known
  - constraints are satisfied at all times t

Ergodic energy management

$$\begin{aligned} J_{2,t}^* := \min_{\{\mathbf{p}_t^g, \mathbf{q}_t^g\}_t} \quad & \mathbb{E}[f_t(\mathbf{p}_t^g, \mathbf{q}_t^g)] \\ \text{s.to} \quad & 0 \leq p_{n,t}^g \leq \bar{p}_{n,t}^g, \ \forall n \\ & (p_{n,t}^g)^2 + (q_{n,t}^g)^2 \leq \bar{s}_n^2, \ \forall n \\ & v_l^B \leq v_{n,t}(\mathbf{p}_t^g, \mathbf{q}_t^g) \leq v_u^B, \ \forall n \\ & \mathbb{E}[(p_{n,t}^g)^2 + (q_{n,t}^g)^2] \leq s_n^2, \ \forall n \\ & v_l^A \leq \mathbb{E}[v_{n,t}(\mathbf{p}_t^g, \mathbf{q}_t^g)] \leq v_u^A, \ \forall n \end{aligned}$$

- Relaxation of deterministic scheme, i.e., $J_{2,t}^* \leq \mathbb{E}[J_{1,t}^*]$
  - expectations over joint distribution of $(\mathbf{p}_t^c, \mathbf{q}_t^c, \bar{\mathbf{p}}_t^g)$ across all t
  - average inverter usage/voltage magnitudes in tighter range
  - instantaneous values in wider range (hard limits imposed)

G. Wang, V. Kekatos, A. Conejo, and G. Giannakis, “Ergodic energy management leveraging resource variability in distribution grids," *IEEE Trans. on Power Systems,* 2016 (http://arxiv.org/abs/1508.00654).

Stochastic approximation solver

- Let $\mathbf{x} := (\{\mathbf{p}_t^g, \mathbf{q}_t^g\}_t)$ and dual variables $\boldsymbol{\nu}, \underline{\boldsymbol{\xi}}, \overline{\boldsymbol{\xi}} \in \mathbb{R}_+^N$

$$\mathcal{L}\left(\mathbf{x}; \boldsymbol{\nu}, \underline{\boldsymbol{\xi}}, \overline{\boldsymbol{\xi}}\right) := \mathbb{E}\Big\{ f_t(\mathbf{p}_t^g, \mathbf{q}_t^g) + \sum_{n=1}^{N} \nu_n \left[(p_{n,t}^g)^2 + (q_{n,t}^g)^2 \right]$$
$$+ \sum_{n=1}^{N} (\overline{\xi}_n - \underline{\xi}_n) v_{n,t}(\mathbf{p}_t^g, \mathbf{q}_t^g) \Big\} - \sum_{n=1}^{N} \left(\nu_n s_n^2 - \underline{\xi}_n v_l^A + \overline{\xi}_n v_u^A \right)$$

- Dual problem

$$g(\boldsymbol{\nu}^*, \underline{\boldsymbol{\xi}}^*, \overline{\boldsymbol{\xi}}^*) := \max_{\boldsymbol{\nu}, \underline{\boldsymbol{\xi}}, \overline{\boldsymbol{\xi}} \geq \mathbf{0}} \mathbb{E}\left[g_t(\boldsymbol{\nu}, \underline{\boldsymbol{\xi}}, \overline{\boldsymbol{\xi}}) \right] - \sum_{n=1}^{N} \left(\nu_n s_n^2 - \underline{\xi}_n v_l^A + \overline{\xi}_n v_u^A \right)$$

  - Stochastic approximation under ergodicity conditions

Primal update: $(\hat{\mathbf{p}}_t^g, \hat{\mathbf{q}}_t^g)$ minimizers of $g_t(\boldsymbol{\nu}_{t-1}, \underline{\boldsymbol{\xi}}_{t-1}, \overline{\boldsymbol{\xi}}_{t-1})$

Dual update: $(\boldsymbol{\nu}_t, \underline{\boldsymbol{\xi}}_t, \overline{\boldsymbol{\xi}}_t)$ using projected subgradient with $\mu > 0$

Convergence

If $H := \sum_{n=1}^{N} \left[s_n^2 + 2(v_u^B - v_l^B)^2\right]$ *, it holds w.p.1 that*

$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=1}^{t} [(\hat{p}_{n,\tau}^g)^2 + (\hat{q}_{n,\tau}^g)^2] \leq s_n^2$$

$$v_l^A \leq \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=1}^{t} v_{n,\tau}(\hat{\mathbf{p}}_\tau^g, \hat{\mathbf{q}}_\tau^g) \leq v_u^A.$$

Further, the incurred operational costs satisfy

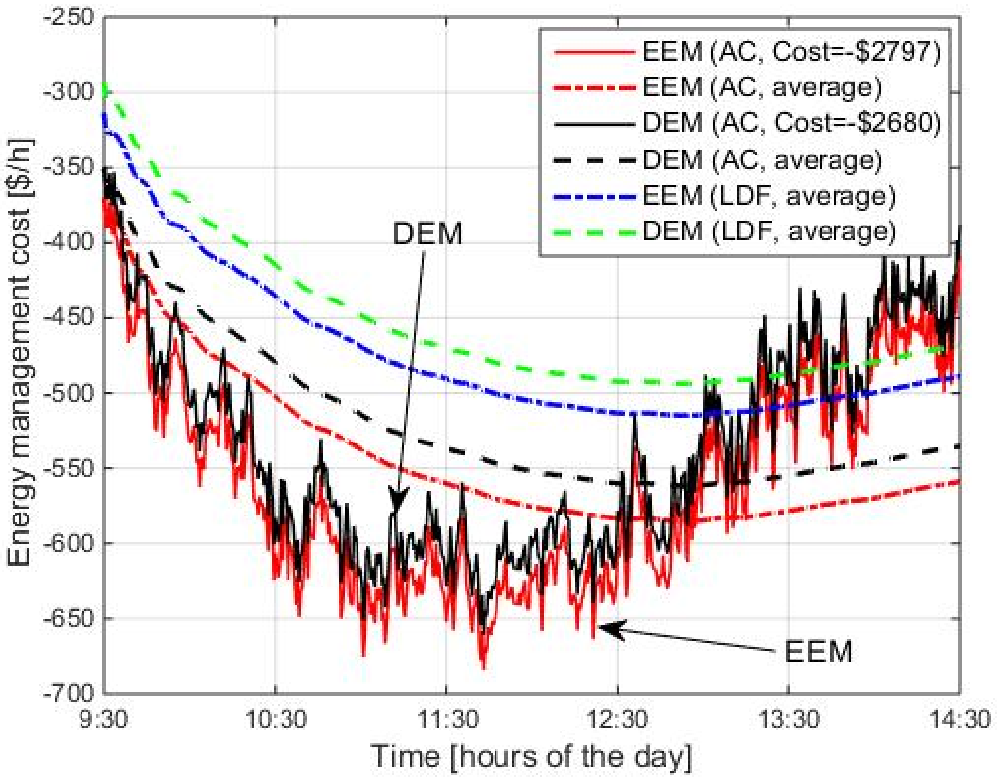
$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=1}^{t} f_t(\mathbf{p}_t^g, \mathbf{q}_t^g) - J_2^* \leq \frac{\mu H^2}{2}.$$

- Feasibility ensured almost surely; at most $\mu H^2/2$ away from optimal J_2^*
- True even if processes are correlated across time

N. Gatsis, A. Ribeiro, and G. B. Giannakis, "A class of convergent algorithms for resource allocation in wireless fading networks," *IEEE Trans. on Wireless Comm.*, pp. 1808-1823, May 2010.

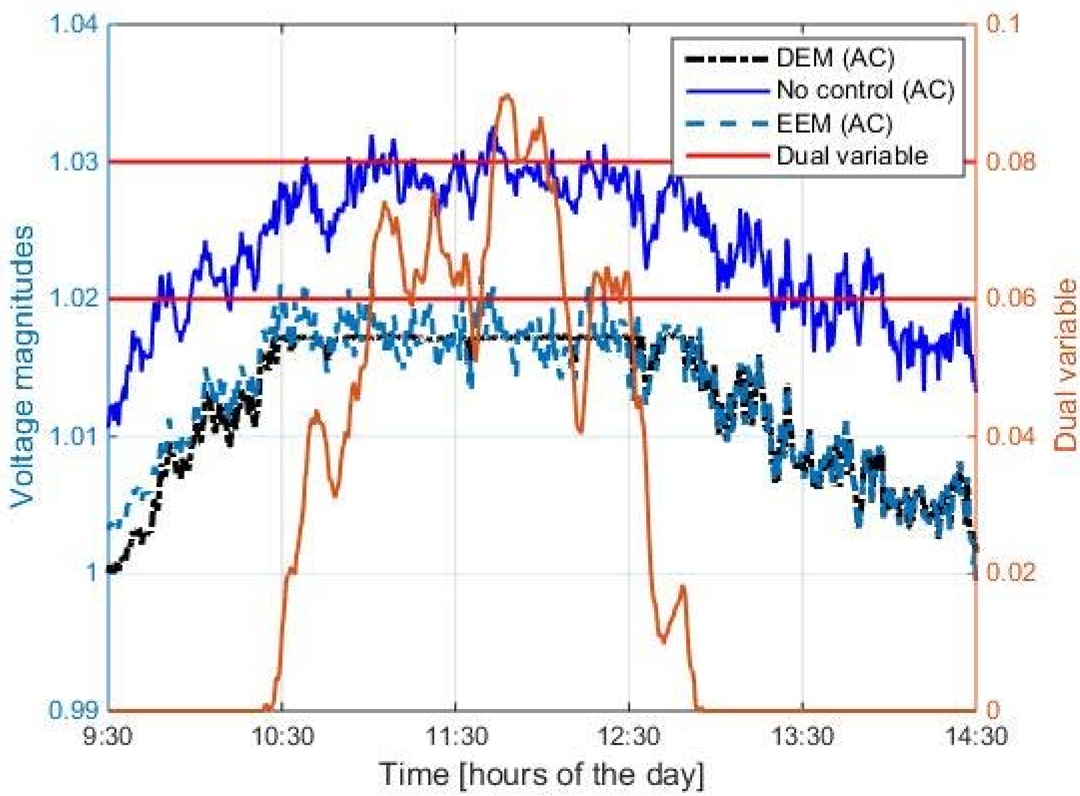
Testing joint ergodic management

- AC branch flow model (SOCP relaxation); and *LinDistFlow* (LDF) approx. model
- SouthCalEd grid: 56 buses and 2 PVs; 30sec real-world load data
- Flexibilities $[v_l^A, v_u^A] = [0.98^2, 1.02^2]$, $[v_l^B, v_u^B] = [0.97^2, 1.03^2]$, $\bar{s} = 1.3s$



S. Barker, A. Mishra, D. Irwin, E. Cecchet, P. Shenoy, J. Albrecht, "Smart*: An open data set and tools for enabling research in sustainable homes," *Wrkshp. on Data Mining Apps. in Sustainability*, Beijing, China, Aug. 2012

Real-time voltage evolution



- Over-voltage effects have short duration
- Dual variable responds to over-voltages quickly

Take-home messages

- Online PSSE
  - Nonconvexity tackled by semidefinite relaxation
  - Online convex optimization learns (un)known dynamics on the fly

- Real-time pricing for demand response
  - Online learning of consumer time-varying demands with sublinear regret

- Stochastic energy management
  - Online power control to accommodate uncertainties and leverage flexibilities

- Research outlook
  - OCO/stochastic approximation for other power system optimization tasks?
  - Big data grid analytics (anomalies, classification and clustering)

Thank you!